ACT Research & Policy

Technical Brief

2016

Relating the ACT Indicator *Understanding Complex Texts* to College Course Grades

Jeff Allen, PhD; Brad Bolender; Yu Fang, PhD; Dongmei Li, PhD; and Tony Thompson, PhD

Introduction

Beginning in fall 2015, student, high school, and college ACT® test score reports will include an indicator for *Understanding Complex Texts*. This indicator measures level of proficiency on a subset of items from the ACT reading test assessing the ability to make global bridging inferences across a range of increasingly complex texts.[1] Student performance will be categorized as Below Proficient, Proficient, or Above Proficient. In this paper, we describe how the cut scores for Proficient and Above Proficient were derived, and how the proficiency levels relate to college course grades.

A two-part study was conducted to:

1. Examine criterion-related evidence for validating ACT's measure of understanding complex texts, and
2. Establish cut scores for ACT's measure of understanding complex texts that predict success in first-year college courses with a high demand for understanding complex texts.

In addition to examining criterion-related validity evidence, the first part of the study informs the selection of the college courses that are used to establish the cut scores.

Description of the *Understanding Complex Texts* Construct

The ACT Understanding Complex Texts measure targets the ability to make global bridging inferences about the range of increasingly complex texts included in the ACT reading test. Items included in the score assess the ability to understand implied connections between details that are at least two sentences apart, a requirement for understanding the central meaning and purpose of texts. Making plausible global bridging inferences indicates that a sufficiently accurate mental representation of textual information is being constructed in a reader's mind. This evidence of deep comprehension reflects an understanding of both explicit and implicit situations rather than merely stated information and is a basis for learning from texts.[2]

Methods

This study uses ACT test data linked to college course grade data.[3] For a sample of previously-administered ACT test forms for which student college course grade data was available, ACT content experts identified a subset of items from the ACT reading test for use in a measure of

Jeff Allen is a statistician in the Research division at ACT. He specializes in longitudinal research linking test scores to educational outcomes and student growth models.

Brad Bolender is a principal assessment specialist in Test Development at ACT specializing in English Language Arts assessments and automated scoring of constructed responses.

Yu Fang is a psychometrician in the Research division at ACT. He specializes in multidimensional IRT and equating.

Dongmei Li is a psychometrician in the Research division at ACT. She specializes in test equating, scaling, and student growth modeling.

Tony Thompson is a psychometrician in the Research division at ACT. His research interests include adaptive testing, measurement precision estimation, and student growth modeling.

Acknowledgment
The authors thank Deborah Harris, Jim Hogan, and Krista Mattern for their suggestions on this paper.

ACT Technical Briefs provide reliability, validity, and other psychometric analyses on ACT education and workforce development assessments, services, and programs and those of its partners. For more on the ACT test, visit www.act.org.

understanding complex texts. The number of items identified varied by test form, ranging from 13 to 18. Scale scores were then derived by equating the raw scores across the different test forms, removing differences due to number of items included and item difficulty. The equated scores range from 0 to 16, and in this paper we refer to these scores as *ACT Understanding Complex Texts scores* (or *UCT scores*). Note that the ACT UCT scores used in this study are not provided on ACT score reports, but are used to classify students into the proficiency levels. Using the reading items from each test form that were not included in the UCT score, another score was developed using the same equating procedures and placed on the 0–16 scale of the UCT score. We refer to these scores as *ACT non-understanding complex texts scores* (or *non-UCT scores*).

Data from 19 first-year college course types were used (Table 1). The course types were chosen to represent a spectrum of demand for understanding complex texts. The sample sizes (number of institutions and number of students) for each course type are provided. Students from both two-year and four-year colleges were included. Similar to other ACT research on college course grade outcomes, the course grade data were provided by postsecondary institutions participating in ACT research services or research partnerships.[4] Courses identified as remedial, developmental, or honors were excluded. Overall, 263,265 students from 439 postsecondary institutions were included and students could be represented in multiple courses. The total sample was 59% female, 41% male, 77% white, 9% African-American, 3% Hispanic, 3% Asian, 4% other race/ethnicity, and 3% unknown race/ethnicity.

Prior to all analyses, the college courses were grouped by a subject matter expert according to their hypothesized demand for understanding complex texts, defined as the level of ability in making global bridging inferences required to achieve a B or higher. Courses were hypothesized to have higher demand if typical coursework has a relatively higher demand for interpreting and integrating the central meaning and purpose of a variety of texts. Courses were hypothesized to have a lower demand for understanding complex texts if coursework typically has a relatively lower demand for interpreting and integrating the central meaning and purpose of a variety of texts, though these courses still typically require students to use complex texts with a greater emphasis on other reading abilities, such as referring to explicit textual information, in their coursework. Twelve course types were believed to have higher demand, four course types were believed to have moderate demand, and three course types were believed to have lower demand.

Table 1. Sample Sizes

Demand for Understanding Complex Texts[5]	Course Type	N_{inst}	$N_{students}$
Higher	American History	144	57,376
	Composition I	367	153,165
	Economics	37	5,661
	Health Sciences	45	22,568
	Literature	37	5,445
	Other History	82	18,382
	Other Natural Science	23	5,271
	Political Science	45	36,256
	Psychology	200	71,547
	Sociology	101	30,721
	Statistics or Probability	52	4,419
	Zoology	24	6,572
Moderate	Biology/Life Sciences	199	46,051
	Engineering	17	3,341
	General Chemistry	116	35,788
	Physics (without Calculus)	45	4,057
Lower	College Algebra	265	73,809
	Computer Science or Programming	55	21,741
	Physics (with Calculus)	18	835

Note: N = 263,265 unique students across 19 courses

Part 1: Criterion-Related Validity Evidence

Analyses were conducted to address three research questions:

1. Are ACT UCT scores predictive of success in first-year college courses?
2. Is the importance of ACT UCT scores (relative to non-UCT scores) for predicting course success greater for courses that have a higher demand for understanding complex texts?
3. Are ACT UCT scores predictive of success in first-year college courses, above and beyond the non-UCT measure of reading skills and high school GPA?

Hierarchical logistic regression analyses were conducted to examine the three research questions, while accounting for clustering of students within institutions.[6] Three models were fit, each with a different set of predictor variables.

- To test whether ACT UCT scores are predictive of success in first-year college courses, **Model 1** included ACT UCT score as the sole predictor.
- To test whether ACT UCT scores are relatively more important for college courses that have a higher demand for understanding complex texts skills, **Model 2** included UCT score and non-UCT score as predictors.
- To test whether ACT UCT scores are predictive of success in first-year college courses, above and beyond the non-UCT measure of reading skills and high school GPA, **Model 3** included UCT score, non-UCT score, and HSGPA as predictors.

Part 2: Establishing a Cut Score for ACT Understanding Complex Texts

One approach to establish cut scores is to choose the score associated with a 50% probability of B or higher in targeted college courses. This is the approach used to establish the ACT College Readiness Benchmarks and the ACT STEM Benchmark.[7] Because the score associated with a 50% probability of B or higher can vary across institutions and courses, the following steps were taken to establish a cut score for the ACT Understanding Complex Texts score:

1. For each course, the sample of students was weighted so that it was the same as the population of the ACT-tested high school cohort of 2014 (in states where the majority of students take the ACT) with respect to ACT Composite score range, HSGPA range, and race/ethnicity.
2. For each course, a hierarchical logistic regression model was fit, such that the intercepts and slopes could vary across institutions. This analysis produced an estimated probability of success for each UCT score, course, and institution.

Table 2. Inter-Correlations

Predictor	1	2	3	4
1. ACT Reading Score	1.000			
2. UCT Score	0.884	1.000		
3. Non-UCT Score	0.944	0.700	1.000	
4. HSGPA	0.390	0.353	0.370	1.000
Mean	21.9	9.2	9.2	3.41
SD	5.4	3.3	3.1	0.52

3. Using the results from step two, the minimum UCT score associated with a 50% or higher probability of success for each institution and each course was identified. This is known as the institution-specific cut score for each course.
4. For each course, the results from step two were weighted so that the sample of institutions represented the population of institutions with respect to enrollment of ACT-tested students at four-year selective, four-year less selective, and two-year colleges. Then, the weighted average of the probabilities across institutions was computed. This step produced a probability of success curve for each course (averaged across institutions).
5. For each course, the results from step three were weighted so that the sample of institutions represented the population of institutions with respect to enrollment of ACT-tested students at four-year selective, four-year less selective, and two-year colleges. The weighted median of the cut scores across institutions was computed. This step produced the cut score for each course.
6. The probabilities from step four results across the targeted courses were averaged. This step produced an overall probability of success curve, averaged across courses and institutions.
7. The median of the cut scores from step five across the targeted courses was calculated. This step produced the typical cut score needed for a 50% or higher chance of earning a B or higher grade in a high-demand text complexity course.

Steps one, two, three, and five use the same methodology as was used for the ACT College Readiness Benchmarks. Steps four, six, and seven are additional steps needed to obtain aggregate probability estimates and cut scores across the seven college course types.

Results

Part 1: Criterion-Related Validity Evidence

Before presenting the regression results, first correlations between variables of interest were examined (Table 2). The ACT UCT score and non-UCT score were expected to have very high correlations with the ACT reading score because they are components of the ACT reading test. Correlations with ACT reading scores were 0.884 for the UCT score and 0.944 for the non-UCT score. The larger correlation for the non-UCT score is probably due to there being more non-UCT items than UCT items (24.6 non-UCT items versus 15.4 UCT items, on average, among the 40-item ACT reading test). As expected, UCT scores and non-UCT scores were highly correlated ($r = 0.700$). Correlations with overall high school GPA are also provided. Means and standard deviations of the predictor variables are provided to describe the study sample. The mean ACT reading score is 21.9, which is slightly higher than the

Table 3. Correlations with Course Grades

	Predictor			
Course Type	ACT Reading Score	UCT Score	Non-UCT Score	HSGPA
Higher UCT Demand				
American History	0.302	0.278	0.283	0.393
Composition I	0.198	0.180	0.184	0.375
Economics	0.218	0.189	0.210	0.347
Health Sciences	0.213	0.199	0.195	0.353
Literature	0.216	0.193	0.204	0.307
Other History	0.349	0.320	0.324	0.433
Other Natural Science	0.230	0.211	0.213	0.403
Political Science	0.284	0.260	0.265	0.387
Psychology	0.295	0.271	0.274	0.401
Sociology	0.252	0.231	0.233	0.366
Statistics or Probability	0.187	0.172	0.169	0.378
Zoology	0.275	0.245	0.261	0.365
Moderate UCT Demand				
Biology/Life Sciences	0.316	0.285	0.298	0.423
Engineering	0.101	0.079	0.099	0.187
General Chemistry	0.228	0.212	0.211	0.361
Physics (without Calculus)	0.219	0.202	0.203	0.389
Lower UCT Demand				
College Algebra	0.187	0.168	0.173	0.400
Computer Science or Programming	0.175	0.164	0.160	0.348
Physics (with Calculus)	0.083	0.051	0.092	0.216

mean ACT reading score among all ACT-tested high school graduates of 2015 (21.4).[8]

For each college course type, correlations of the predictors with course grades are provided in Table 3.[9] For all course types except Physics with Calculus, ACT reading score had higher correlations than either the UCT score or non-UCT score. Because the ACT reading score is more reliable than either component score, this result was expected. For the UCT score and non-UCT score, correlations with college course grades were very similar. Consistent with prior studies, high school GPA had the largest correlations with college course grades. The correlations in Table 3 describe the strength of the relationship between the predictors and college grades, but are limited because 1) they do not account for clustering of students within institutions; 2) inference of the correlation is limited when the dependent variable (college grades) is not continuous; and 3) the correlation does not control for the effects of other predictors. For these reasons, hierarchical logistic regression models were fit.

Hierarchical logistic regression models were used to address the three research questions of interest, while accounting for clustering of students within institutions. Three models were fit, each with a different set of predictor variables (Table 4).

Because all regression coefficients for UCT score from Model 1 are positive and statistically significant ($p < 0.05$), UCT scores are predictive of success in first-year college courses (Research Question 1). The predictive strength is greatest for Other History ($B = 0.672$) and smallest for Engineering ($B = 0.198$). The coefficients represent the change in the log-odds of success (earning a B or higher) for each standard deviation increase in the predictor. For example, the odds of earning a B or higher in American History increase by a factor of 1.75 for each standard deviation increase in ACT UCT score.[10]

In Model 2, the predictive strength of UCT score and non-UCT score are compared by fitting regression models that use both measures as predictors. For most course types, the regression coefficients are very similar. The regression coefficient for the non-UCT score is noticeably larger

Table 4. Logistic Regression Coefficients, B or Higher Grades

		Model 1		Model 2		Model 3	
Course Type	Predictor	B	SE	B	SE	B	SE
Higher UCT Demand							
American History	UCT Score	0.557	0.010	0.331	0.013	0.246	0.013
	Non-UCT Score			0.344	0.013	0.223	0.013
	HSGPA					0.711	0.011
Composition I	UCT Score	0.318	0.006	0.188	0.008	0.108	0.008
	Non-UCT Score			0.211	0.008	0.100	0.008
	HSGPA					0.707	0.007
Economics	UCT Score	0.460	0.031	0.256	0.040	0.180	0.042
	Non-UCT Score			0.308	0.040	0.182	0.042
	HSGPA					0.700	0.036
Health Sciences	UCT Score	0.409	0.017	0.254	0.022	0.160	0.023
	Non-UCT Score			0.243	0.022	0.114	0.023
	HSGPA					0.598	0.018
Literature	UCT Score	0.470	0.034	0.285	0.045	0.219	0.046
	Non-UCT Score			0.285	0.045	0.213	0.046
	HSGPA					0.551	0.035
Other History	UCT Score	0.672	0.018	0.398	0.023	0.301	0.024
	Non-UCT Score			0.422	0.023	0.285	0.024
	HSGPA					0.792	0.021
Other Natural Science	UCT Score	0.381	0.033	0.228	0.041	0.140	0.043
	Non-UCT Score			0.248	0.041	0.124	0.043
	HSGPA					0.733	0.037
Political Science	UCT Score	0.562	0.012	0.327	0.016	0.235	0.016
	Non-UCT Score			0.371	0.016	0.256	0.017
	HSGPA					0.720	0.014
Psychology	UCT Score	0.547	0.009	0.326	0.011	0.248	0.012
	Non-UCT Score			0.348	0.012	0.235	0.012
	HSGPA					0.732	0.010
Sociology	UCT Score	0.457	0.014	0.279	0.018	0.200	0.019
	Non-UCT Score			0.280	0.018	0.182	0.019
	HSGPA					0.626	0.015
Statistics or Probability	UCT Score	0.351	0.035	0.206	0.045	0.135	0.047
	Non-UCT Score			0.225	0.045	0.128	0.047
	HSGPA					0.661	0.040
Zoology	UCT Score	0.602	0.028	0.370	0.037	0.322	0.039
	Non-UCT Score			0.350	0.037	0.267	0.039
	HSGPA					0.823	0.036
Moderate UCT Demand							
Biology/Life Sciences	UCT Score	0.585	0.011	0.319	0.014	0.231	0.015
	Non-UCT Score			0.413	0.014	0.283	0.015
	HSGPA					0.859	0.014

Table 4. (continued)

		Model 1		Model 2		Model 3	
Course Type	Predictor	B	SE	B	SE	B	SE
Engineering	UCT Score	0.198	0.050	*0.061*	0.070	*-0.015*	0.071
	Non-UCT Score			0.195	0.068	0.148	0.070
	HSGPA					0.411	0.049
General Chemistry	UCT Score	0.409	0.012	0.236	0.015	0.163	0.016
	Non-UCT Score			0.260	0.016	0.175	0.016
	HSGPA					0.712	0.014
Physics (without Calculus)	UCT Score	0.369	0.037	0.246	0.050	0.163	0.053
	Non-UCT Score			0.185	0.050	*0.066*	0.053
	HSGPA					0.743	0.043
Lower UCT Demand							
College Algebra	UCT Score	0.315	0.008	0.176	0.010	0.083	0.011
	Non-UCT Score			0.216	0.010	0.087	0.011
	HSGPA					0.822	0.010
Computer Science or Programming	UCT Score	0.354	0.016	0.222	0.021	0.114	0.022
	Non-UCT Score			0.207	0.021	0.053	0.022
	HSGPA					0.676	0.018
Physics (with Calculus)	UCT Score	0.289	0.077	*0.129*	0.102	*0.069*	0.106
	Non-UCT Score			0.241	0.101	*0.200*	0.105
	HSGPA					0.577	0.091

B = standardized logistic regression coefficient, SE = standard error of coefficient. Non-significant coefficients ($p > 0.05$) are italicized.

for Economics, Biology/Life Sciences, Engineering, and Physics with Calculus. The regression coefficient for the UCT score is noticeably larger for Physics without Calculus.

Overall, from Model 2, ACT UCT scores appear to be more important for course types believed to have higher understanding complex texts demand as compared to course types believed to have lower demand. The mean coefficient is 0.287 for the twelve course types with the highest demand, 0.215 for the four course types with moderate demand, and 0.176 for the three course types with lower demand. The mean coefficient for non-UCT score is 0.303 for the twelve course types with the highest demand, 0.263 for the four course types with moderate demand, and 0.221 for the three course types with lower demand. Therefore, there is some evidence that ACT UCT scores are relatively more important for college course types that are believed to demand greater understanding complex texts skills. More often than not, the non-UCT score is more predictive than the UCT score. One reason for this is that the non-UCT score is based on more test items, and so should have greater reliability.[11]

Model 3 examines the predictive strength of the UCT score and non-UCT score after adjusting for high school GPA. Typically, high school GPA is the strongest predictor of first-year college grades and validity arguments for test scores (e.g., ACT scores) are strengthened by showing that the test scores are significant predictors, after accounting for high school GPA. With the exception of Engineering and the Physics courses, all three variables are significant predictors of college course success. For Engineering, the UCT score was not a significant predictor. For Physics without Calculus, the non-UCT score was not a significant predictor. For Physics with Calculus, neither score was a significant predictor. For the other course types, UCT scores are predictive of success, above and beyond the non-UCT measure of reading skills and high school GPA.

In Model 3, the mean coefficient for UCT score is 0.208 for the twelve course types with the highest demand, 0.136 for the four course types with moderate demand, and 0.089 for the three course types with lower demand (Table 5). Model 3 provides further evidence that ACT UCT scores are relatively more important for college course types that demand greater understanding complex texts skills.

Because Model 3 includes both HSGPA and non-UCT score as predictors, it provides the most stringent test of the incremental validity of the UCT score, and was therefore used as the basis for selecting courses to include in the cut score analysis. Based on the criterion-related validity evidence presented in Table 5, the following course types were used to develop a cut score for Understanding Complex Texts:

- American History*
- Literature
- Other History*
- Other Natural Science
- Physics (without Calculus)
- Sociology*
- Zoology

Six of the seven course types (all but Physics without Calculus) were hypothesized to have higher demand for understanding complex texts skills. For all seven course types, the Model 3 regression analysis showed that the UCT score was modestly more important than the non-UCT score for predicting grades of B or higher. Three of the seven course types (marked with *) were also used to develop the ACT Reading Benchmark. Note that the Health Science course type was considered, but not chosen because the course titles within Health Sciences suggested too much heterogeneity in course content (e.g., course titles included health and personal wellness, first aid, nutrition, and medical terminology). There was some evidence that ACT UCT scores were also relatively more important than non-UCT scores for Psychology, Composition I, and Statistics or Probability. However, these courses were not selected for the cut score study because their beta weights for the UCT score were relatively small.

Table 5. Summarizing Model 3 Regression Coefficients

	Predictor		
Course Type	UCT Score	Non-UCT Score	Diff
American History	0.246	0.223	0.022
Composition I	0.108	0.100	0.008
Economics	0.180	0.182	-0.002
Health Sciences	0.160	0.114	0.046
Literature	0.219	0.213	0.006
Other History	0.301	0.285	0.015
Other Natural Science	0.140	0.124	0.016
Political Science	0.235	0.256	-0.021
Psychology	0.248	0.235	0.013
Sociology	0.200	0.182	0.018
Statistics or Probability	0.135	0.128	0.007
Zoology	0.322	0.267	0.055
Higher UCT Demand Average	0.208	0.192	0.015
Biology/Life Sciences	0.231	0.283	-0.052
Engineering	-0.015	0.148	-0.163
General Chemistry	0.163	0.175	-0.011
Physics (without Calculus)	0.163	0.066	0.097
Moderate UCT Demand Average	0.136	0.168	-0.032
College Algebra	0.083	0.087	-0.004
Computer Science or Programming	0.114	0.053	0.061
Physics (with Calculus)	0.069	0.200	-0.131
Lower UCT Demand Average	0.089	0.113	-0.025

Table 6. Distributions of Institution-Specific Cut Scores

Course Type	N	25th Percentile	Median	75th Percentile
American History	112	9	10	11
Literature	20	4	6	7
Other History	48	8	9	10
Other Natural Science	15	6	8	10
Physics (without Calculus)	25	9	10	12
Sociology	73	5	8	9
Zoology	19	9	12	13
Median Across Courses		8	9	10

Part 2: Establishing a Cut Score for ACT Understanding Complex Texts

Table 6 summarizes the distributions of institution-specific cut scores for each course types. There is considerable variation in median cut scores across course types. At one extreme, a UCT score of 6 is needed to have a 50% probability of earning a B or higher in Literature at the typical postsecondary institution. At the other extreme, a UCT score of 12 is needed to have a 50% probability of earning a B or higher in Zoology at the typical postsecondary institution. This variation suggests that the UCT cut score will be sensitive to the choice of courses used to establish the cut score.

For each course type, there is also variation across institutions in cut scores. For example, for Sociology, the 25th percentile cut score was 5 and the 75th percentile was 9.

One way to obtain an overall UCT score is to use the median of the course-specific median cut scores. The median is 9, and this can be used to set an **overall UCT cut score of 9**.

Figure 1 shows probability of success curves for each course type (obtained from step 4 described in the Methods section). Similar to Table 6, the figure shows differences across course types. Literature (dark blue line) is the "easiest" course as students have higher probabilities of success (overall, 71% were successful in Literature). Zoology is the most difficult course (overall, 51% were successful).

Using the probability of success curves for each course type, we can find the UCT scores related to varying probabilities of success (Table 7).

Figure 2 shows the probability of success curves obtained by averaging the probability curves across the seven course types (step 6 described in Methods section). In addition

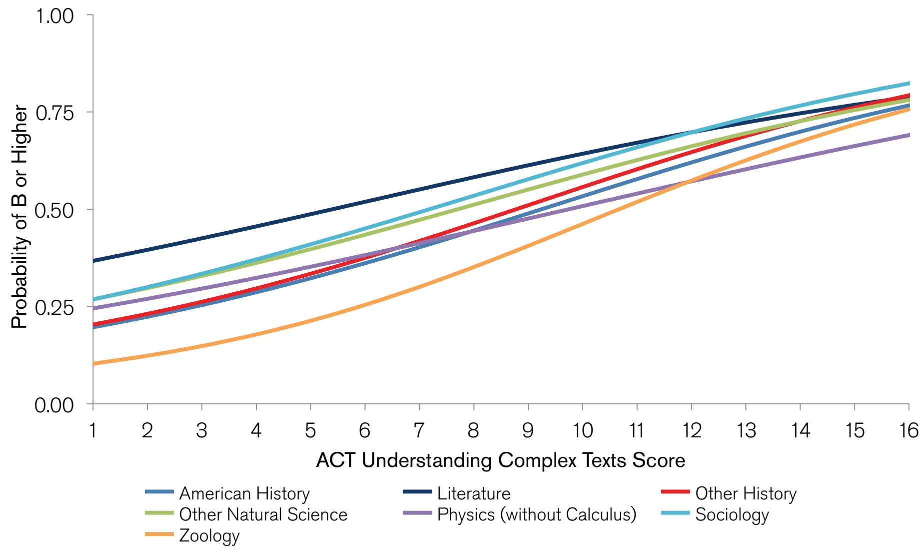

Figure 1. Probabilities of success by UCT score

Table 7. UCT Scores Related to Different Probabilities of Success

	Probability of Success				
Course Type	0.25	0.33	0.50 (Proficiency Cut Score)	0.67	0.75
American History	3	6	10	14	16
Literature	1	1	6	11	15
Other History	3	5	9	13	15
Other Natural Science	1	4	8	13	15
Physics (without Calculus)	2	5	10	16	16
Sociology	1	3	8	12	14
Zoology	6	8	12	14	16
Median Across Courses	2	5	9	13	15

to the probability curve for the B or higher criterion, curves are also shown for C or higher and A.

For B or higher, a UCT score of 8 is related to a mean probability of 0.476, while a UCT score of 9 is related to a mean probability of 0.518. Because 9 is the first score above the 0.50 threshold, this result is consistent with the overall UCT cut score of 9 reported earlier.

The probability of success curves can also be used to inform the choice of a cut score for "Above Proficient." For example, from Table 7, we see that a UCT score of 13 is the median score across courses related to a 0.67 probability of earning a B or higher. From Figure 2, a UCT score of 13 is related to a 0.37 mean probability of earning an A and a 0.85 mean probability of earning a C or higher.

A UCT score of 13 was chosen as the Above Proficient cut score. The standard error of measurement of the UCT score varies by test form, but is typically close to 2. Therefore, a UCT score of 13 is about two standard error of measurement above the Proficient cut score (9). For students who score at the Above Proficient cut score, we are reasonably certain that their true performance level is above the Proficient cut score.

Students who meet the ACT Reading Benchmark are likely to also meet the proficient cut score for UCT (Table 8). Among those who met or exceeded the ACT Reading Benchmark in the study sample, 83% met or exceeded the UCT proficient cut score. Among those who did not meet or exceed the ACT Reading Benchmark, only 12% met or exceeded the UCT proficient cut score. Overall, 14% of the study sample had differentiated classifications (below proficient on UCT but met the reading Benchmark, or proficient or above on UCT but did not meet the ACT Reading Benchmark). Compared to the percentage of students meeting the ACT Reading Benchmark (51%), fewer students met the UCT proficient (or above) cut score (48%).

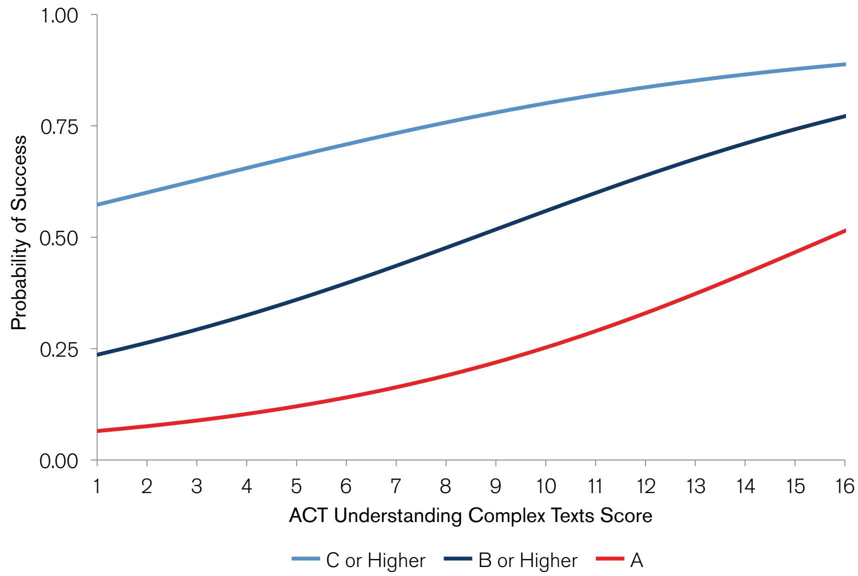

Figure 2. Mean probability of success by UCT score

Table 8. Cross-Classification of Meeting ACT Reading Benchmark and UCT Proficiency Levels

	UCT Proficiency Level			
Met ACT Reading Benchmark?	Below Proficient (0–8)	Proficient (9–12)	Above Proficient (13–16)	Total
No (1–21)	112,770	14,915	210	127,895
Yes (22–36)	22,937	72,478	39,955	135,370
Total	135,707	87,393	40,165	263,265

Summary

A two-part study was conducted to:

1. Examine criterion-related evidence for validating ACT's measure of understanding complex texts, and
2. Establish Proficient and Above Proficient cut scores for ACT's measure of understanding complex texts that predict success in first-year college courses that have a high demand for understanding complex texts.

The first part of the study informed the selection of the college course types that were used to establish the cut scores.

We found evidence that ACT's measure of understanding complex texts is relatively more predictive of success in college course types that have higher demands for understanding complex texts. College course types for which ACT's measure of understanding complex texts was more predictive (relative to a non-understanding complex texts measure of reading skills) include American History, Literature, Other History, Other Natural Science, Physics (without Calculus), Sociology, and Zoology. Outcomes from these course types were used to establish the cut scores.

The Proficient cut score was chosen to be the median score (across the seven courses) associated with a 50% chance of earning a B or higher at the typical institution. Averaging across courses, the Proficient cut score is also associated with a 78% chance of earning a C or higher grade and a 22% chance of earning an A.

The Above Proficient cut score was chosen to be the median score (across the seven courses) associated with a 67% chance of earning a B or higher at the typical institution. Averaging across courses, the Above Proficient cut score is also associated with an 85% chance of earning a C or higher grade and a 37% chance of earning an A. The Above Proficient cut score is also two standard error of measurement above the Proficient cut score.

Notes

1 www.act.org/actnext/. Bridging inferences are those that depend exclusively on connections between textual information, as opposed to connections between textual information and prior knowledge, and the global distinction is made to indicate inferences connecting multiple pieces of text information that are separated by at least one sentence. Generally, less-skilled readers tend to focus more on the immediate context surrounding each sentence, while skilled readers are more likely to make connections between ideas across a text to develop a coherent global representation. Thus, demonstrating the ability to make global bridging inferences represents specific evidence of a reader achieving deep understanding of underlying meaning in the context of a reading assessment, where a goal is to minimize the effect of prior knowledge. McNamara, D. S., & Magliano, J. (2009). Toward a comprehensive model of comprehension. *Psychology of learning and motivation*, 51, 297–384; Millis, K., & Magliano, J. (2012). Assessing comprehension processes during reading. *Reaching an understanding*, 35–54; O'Brien, E. J., Cook, A. E., & Lorch, R. F. (2015). *Inferences during Reading.* Cambridge University Press.

2 McNamara, D. S., & Magliano, J. (2009). Toward a comprehensive model of comprehension. *Psychology of learning and motivation*, *51*, 297–384; van Dijk, T., & Kintsch, W. (1983). *Strategies of discourse comprehension.* New York: Academic Press.

3 ACT collects college course grade data through the ACT Course Placement Service (www.act.org/research/services/crsplace/) and the ACT Admissions service (www.act.org/research/services/admissions/).

4 Allen, J. (2013). *Updating the ACT College Readiness Benchmarks* (ACT Research Report Series No. 2013-6). Iowa City, IA: ACT, Inc; Lorah, J. E., & Ndum, E. (2013). *Trends in Achievement Gaps in First-Year College Courses For Racial/Ethnic, Income, and Gender Subgroups: A 12-Year Study.* (ACT Research Report No. 2013-8). Iowa City, IA: ACT, Inc; Mattern, K., Radunzel, J., & Westrick P. (2015). *Development of STEM readiness benchmarks to assist career and educational decision making.* (ACT Research Report No. 2015-3). Iowa City, IA: ACT, Inc; Westrick, P.A. & Allen, J. (2014). *Validity evidence for ACT Compass Placement Tests.* (ACT Research Report No. 2014-2). Iowa City, IA: ACT, Inc.

5 Hypothesized demand for understanding complex texts.

6 Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models.* Thousand Oaks, CA: Sage Publications.

7 Radunzel, J., Mattern, K., Crouse, J., & Westrick P. (2015). *Development and Validation of a STEM Benchmark Based on the ACT STEM Score.* ACT Technical Brief. Iowa City, IA: ACT, Inc.

8 ACT, Inc. (2015). *The ACT Profile Report – National. Graduating Class 2015.* Iowa City, IA: ACT, Inc.

9 Course grades are on the usual 0.0 (F) to 4.0 (A) scale. Course withdrawals were coded as 0.0.

10 exp(0.557) = 1.75.

11 For example, for American History, the beta weight for UCT score is 0.331 and the beta weight for non-UCT score is 0.344. On average, UCT scores included 15.4 items while non-UCT scores included 24.6 items. The typical reliability of the ACT reading test is 0.88, and using the Spearman-Brown formula the average reliability of the UCT and non-UCT scores are predicted to be 0.74 and 0.82, respectively. Measurement-error corrected beta weights for American History can then be approximated as 0.385 for UCT score and 0.380 for non-UCT score.